California Energy Commission

CONSULTANT REPORT

Projected Electric Vehicle Hourly Loads for the 2017 California Energy Demand Forecast

Prepared for: **California Energy Commission**
Prepared by: **Lawrence Berkeley National Laboratory**

BERKELEY LAB

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Edmund G. Brown Jr., Governor

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ABSTRACT

In 2030, more than 1.5 million plug-in electric vehicles will be on the road, according to the California Energy Commission. As transportation is progressively electrified, an increasing burden is shifted to the power grid. This study estimates the new power demand induced by plug-in electric vehicles from 2015 to 2030.

In this study, the authors consider hybrids and fully electric vehicles for a wide range of types including compact car and sport-utility vehicles. The study considers the development of charging infrastructures, human behavior toward plugging their vehicles, ambient temperature, Californians' typical commute patterns, and multiple time-of-use tariff adoption rates.

This project led to the development and the validation of an agent-based simulation tool. Each vehicle (agent) is associated with a car model representative of on-road consumptions, as well as unique itineraries from the 2009 National Household Travel Survey. Leveraging this bottom-up approach, human behaviors are modeled in the decision of when and where a vehicle will be plugged, based on state of charge, electricity prices, and available charging infrastructures. The method also includes environmental factors such as ambient temperature.

The software output power demand curves from plug-in electric vehicles at various locations specified in the National Household Travel Survey codebook. Overall, the study shows an added 3 gigawatts of power demand from plug-in electric vehicles at 8 p.m. on the grid in 2030. Thus, plug-in electric vehicles cause a 6 percent peak demand increase in the California Independent System Operator service area in 2030. As plug-in electric vehicles growth could be geographically concentrated, this study suggests that it is necessary to look at power system constraints at the transmission and distribution levels to understand the full impact on the grid of plug-in electric vehicle.

Keywords: Plug-in electric vehicles, load forecast, California, power demand

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EXECUTIVE SUMMARY

This study estimates the power demand induced by plug-in electric vehicles from 2015 to 2030 on the power system in California. The project led to the development and the validation of an agent-based simulation tool.

Chapter 1: Historical Demand From Plug-In Electric Vehicles

This chapter describes the work led by Idaho National Laboratory to characterize plug-in electric vehicle charging behavior from real-world data. This work characterizes the difficulty of simulating load profiles at charging stations based on electricity price and location.

Chapter 2: Validation of the Forecasting Software

This chapter shows the validation process used for the simulation tool. The real-world data collected and described in Chapter 1 was split into a training and a validation set. The training set was used to calibrate the simulation tool, and the validation set to verify that given the right vehicle mix and itineraries the simulation tool provides accurate load demand profiles. The validation of the tool was successful from Idaho and Lawrence Berkeley National Laboratories' points of view.

Chapter 3: Method Behind the Forecast

This chapter describes the full method behind the simulation tool. The sections of this chapter cover the type of inputs needed and related formats, the travel itinerary data used to represent driving patterns, the modeling of on-road consumption, charging stations, and time-of-use pricing participation.

Chapter 4: Simulation Results

In this chapter, the major findings of this study, sensitivity analyses, and shortcomings of the simulation are laid out. The results of the forecast include demand profiles on a minute basis from 2015 to 2030 for 21 forecasting zones and three time-of-use adoption rates. To gain confidence in the results, the study looks at the effect of ambient temperature, vehicle mix, charging station mix, and distance traveled on the final results. To give accurate estimations, the model relies on the knowledge of charging station availability at different locations, which is challenging.

Chapter 5: Conclusion

Overall, the study shows an added 3 gigawatts of power demand from plug-in electric vehicles at 8 p.m. on the grid in 2030. Thus, plug-in electric vehicles contribute to a 6 percent increase of the peak demand in the California Independent System Operator balancing area in 2030. As plug-in electric vehicles growth could be geographically concentrated, this study suggests that it is imperative to look at power system constraints at the transmission and distribution levels to calculate the full effect of plug-in electric vehicles.

CHAPTER 1: Historical Plug-In Electric Vehicle Charging Demand From Charging Units in California

Characterization of Plug-In Electric Vehicle Charging Behavior From Real-World Data

Beginning in 2017, the California Energy Commission's energy demand forecasts integrate long-term hourly load projections with the traditional annual forecasts. The hourly projections require adjustments to the load attributable to key demand modifiers, including plug-in electric vehicles (PEVs). For this purpose, PEV charging behavior was characterized using actual charging data from Blink and ChargePoint brand electric vehicle supply equipment (EVSE) in California. This analysis used charging data from several thousand residential and public EVSE, collected from December 2012 to December 2013. In this analysis, the EVSE were divided into groups based on geographic region and EVSE type. Subsequently, the research team created characteristic curves for each group. Details of each of these activities are described in the following section.

Electric Vehicle Supply Equipment Grouping

The research team first grouped EVSE geographically by Energy Commission's forecast zones. There were sufficient data to generate characteristic curves for the following 13 forecasting zones: Greater Bay Area, North Coast, Central Valley, Central Coast, Los Angeles Metro, Big Creek West, Northeast, Eastern, San Diego Gas & Electric (SDG&E), Sacramento Municipal Utility District (SMUD), Los Angeles Department of Water and Power (LADWP) Coastal, LADWP Inland, and Burbank-Glendale. The research team generated the characteristic curves for a given forecasting zone if there were at least 10 EVSE used to create the characteristic curves. The team then sub-grouped EVSE in each forecasting zone based on one of the following EVSE types:

- Public EVSE – All publicly accessible alternating current (AC) Level 2 (L2) EVSE in the dataset ranging from 3 kilowatts (kW) to 20 kW, as opposed to Level 1 (L1) that are 1.4 kW. An L1 charger includes typical household outlets found at a residence and an L2 charger requires the installation of charging equipment.
- Residential EVSE – All AC L2 EVSE in the dataset that are at a home.
- Residential EVSE with Leaf – All AC L2 EVSE in the dataset that are at a home with a Nissan Leaf.
- Residential EVSE with Volt – All AC L2 EVSE in the dataset that are at a home with a Chevy Volt.

Definition of Characteristic Curves

The characteristic curves, created from real-world charging data, are chronological curves with 15-minute time steps during the period from December 2012 to December 2013. Below is a description of the characteristic curves that were created for each group of EVSE.

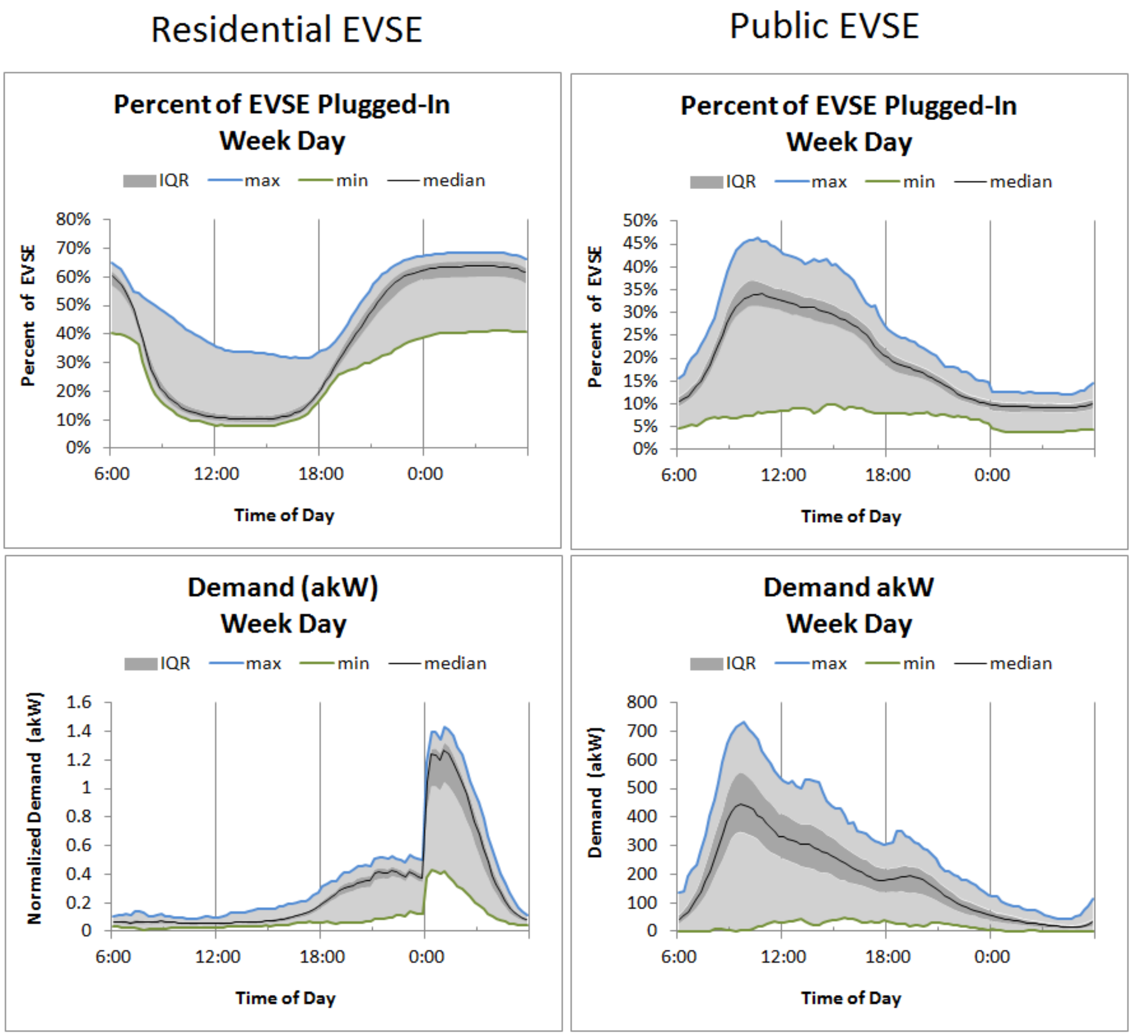
- Installed EVSE
  - The number of EVSE of a certain type installed in the forecasting zone versus time.
  - In some cases, the number decreases over time because EVSE were uninstalled due to technical problems or other reasons.
- Percentage of EVSE Plugged-In
  - The percentage of EVSE in the group connected to an electric vehicle at a given time of day.
- Percentage of EVSE Charging
  - The percentage of EVSE in the group connected to an electric vehicle that is charging at a given time of day.
- Demand (akW)
  - The total demand of all EVSE in the group, expressed as average power (akW).
  - The demand for the residential EVSE is normalized by the total number of residential EVSE, so the demand can be interpreted as a per-EVSE demand.
  - The demand for the public EVSE is not normalized and is the actual total demand.
- Peak Demand (kW)
  - The peak demand is the coincidental peak demand in kW. Coincident demand is the energy demand required by a given customer or class of customers during a particular time period. Coincident peak demand is the energy demand by that group during periods of peak system demand. It refers to demand among a group of customers that coincides with total demand on the system at that time.
  - The peak for a 15-minute segment is calculated as the maximum one-minute average power over the 15-minute segment.

General Results

Characteristic curves were generated in two forms: time-of-day (TOD) plots and "8760" plots. In "8760" plots, every day in the reporting period is shown. TOD plots abbreviate the "8760" plots by showing only a 24-hour period. Variation in the percentage of EVSE plugged in or the demand at a given time across all the days in the reporting period is shown.

Figure 1 shows the percentage of EVSE plugged-in and demand TOD plots for the residential (left) and public (right) EVSE groups in the Greater Bay Area forecasting zone. Daily charging behavior and resulting demand are starkly different between residential and public EVSE. While the demand for the residential EVSE is a normalized, per-EVSE demand, the demand for the public EVSE is an aggregate, or combined, demand, which affects the y-axis scale of the plots but not the shape.

Figure 1: Percentage of EVSE Plugged-In and Demand, Time-of-Day Plots for the Residential (Left) and Public (Right) EVSE Groups in the Greater Bay Area Forecasting Zone



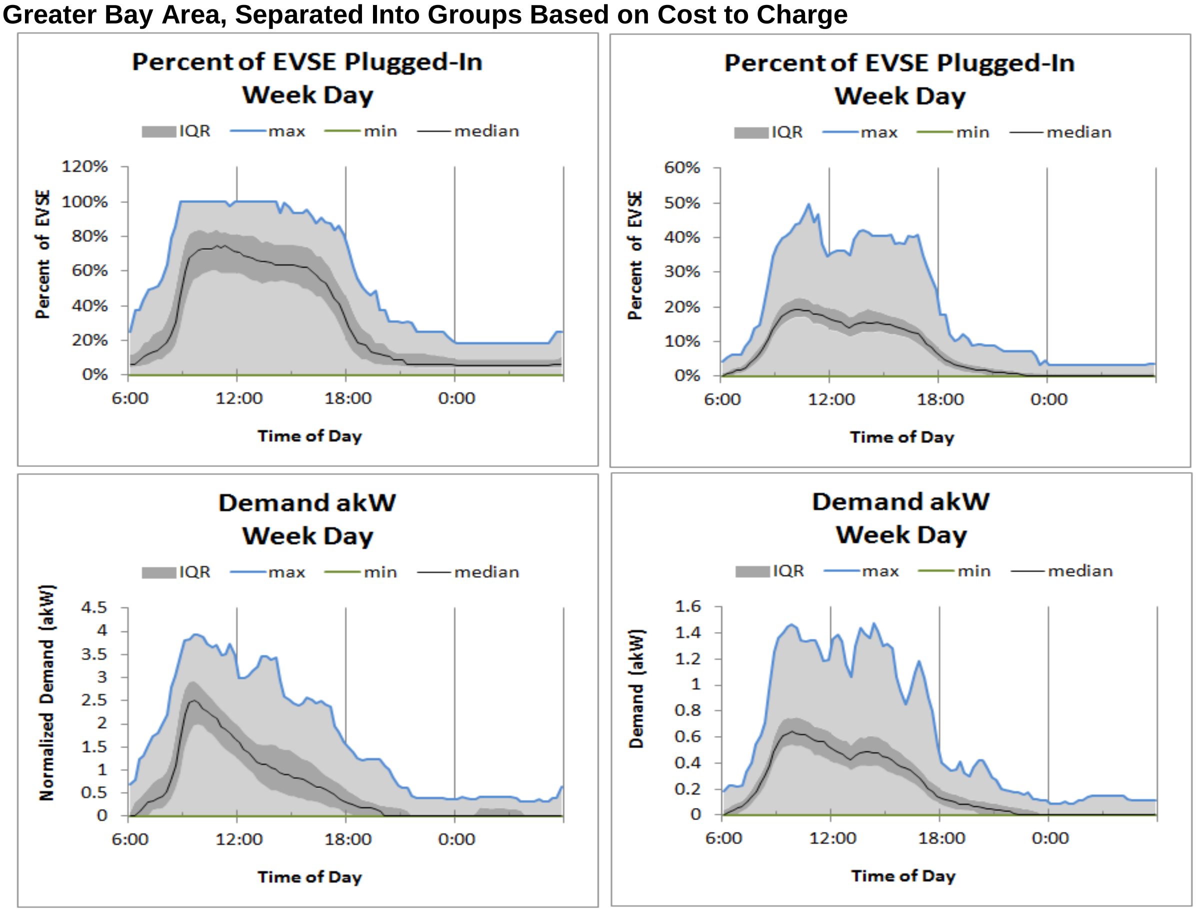
Source: Idaho National Laboratory

Public Charging Cost Sensitivity Results

For publicly accessible EVSE, the question arose as to how cost to use EVSE affects use and grid demand. During the reporting period, the Blink Network offered free and at-cost charging, based on the discretion of the charging station owner. For EVSE with fees for charging, the cost ranged from $0.50 to $2.00 per hour connected to the EVSE. Unfortunately, data on the specific cost setting for each EVSE were not tracked. Therefore, to address the question of cost in this study, EVSE were grouped according to whether they were free or not free to use.

Figure 2 shows the percentage of EVSE plugged-in and demand curves for public EVSE in the Greater Bay Area, separated into groups based on cost to charge. The two figures on the left correspond to free public EVSE. The right two figures correspond to public EVSE that were not free. Although the shapes of the curves are similar, there was a large difference in the magnitude of use between the free and not-free EVSE in the Greater Bay Area. This difference is attributed to cost and because the distribution of venue types where the EVSE in the two groups were installed were not equal. In the Greater Bay Area, almost all the free EVSE were installed at workplaces, whereas the not-free EVSE were installed at many venue types (workplace, retail, education, business offices, and others). EVSE at workplaces typically see higher use, on average, than EVSE at other venue types. Therefore, the effects of cost on customer usage are confounded by effects of venue type. For reference, venue information for both groups of EVSE are included in the files containing the detailed results.

Figure 2: Percentage of EVSE Plugged-In and Demand Curves for Public EVSE in the Greater Bay Area, Separated Into Groups Based on Cost to Charge



Source: Idaho National Laboratory

CHAPTER 2: Validation Using Real-World Data

Introduction

Idaho National Lab (INL) worked with the Lawrence Berkeley National Laboratory (LBNL) to validate the PEV load simulation tool "V2G-Sim" described in Chapter 3. The validation involved using real-world charging data from the San Diego Gas & Electric Company, Pacific Gas and Electric, and Los Angeles service areas collected from the Electric Vehicle Project (EV Project), a different project led by INL.[1]

The EV Project is one of the largest deployment and evaluation projects of electric drive vehicles and charging infrastructure to date. The data collection phase ran for three years (2011 to 2013) and captured almost 125 million miles of driving and 4 million charging events. More than 12,000 alternative current (AC) L2 (208-240V) charging units and more than 100 dual-port direct current (DC) fast chargers were deployed in 20 metropolitan areas. Roughly 8,300 Nissan LEAF™, Chevrolet Volts, and Smart Fortwo electric drive vehicles were also enrolled in the project.

The goal of this validation is to compare the V2G-Sim load demand forecast with the actual power demand measurement from the same set of PEVs.

This validation work is necessary to gain confidence in the software forecasts and to identify the parameters with the most influence on the results. V2G-Sim should be able to forecast past situations before forecasting hypothetical scenarios.

Validation Use Cases

The research team is conducted the validation for six use cases. The use cases were picked to cover different:

- Vehicle types.
- Periods.
- Geographic locations

The use cases were limited by the available data from the EV Project. The validation cases do not cover rural areas, all the seasons, vehicles with longer driving range, or TOU pricings.

Nonetheless, the use cases selected provide a reference for the times of year when PEVs might have a substantial effect on the grid in cities with high levels of PEV penetration using common vehicle models.

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1 https://avt.inl.gov/project-type/ev-project.

Detailed Results

The research team created spreadsheets containing the information described above for each of the 13 Energy Commission forecasting zones with more than 10 EVSE reporting data in the reporting period. An additional set of spreadsheets was created for each of the forecasting zones with more than 10 free EVSE and 10 not-free EVSE reporting data. These spreadsheets can be found on the DVD accompanying this report.

Table 1: Validation Cases per Period, Region, and Vehicle Type

ID	Period*	City	Vehicle
1	Mar_2013	San Francisco	Leaf
2	Aug_2013	San Francisco	Leaf
3	Mar_2013	San Diego	Leaf
4	Mar_2013	San Diego	Volt
5	Aug_2013	Los Angeles	Leaf
6	Aug_2013	Los Angeles	Volt

Source: Lawrence Berkeley National Laboratory, Grid Integration Group

* Only weekdays in specified periods were used because they show a higher charging activity and occur more often.

Future work should include use cases from multiple months, as well as including weekend travel patterns and a variety of TOU pricings.

V2G-Sim Input Definitions

The following inputs were given to V2G-Sim to describe the charging behavior of all the PEVs in each use case.

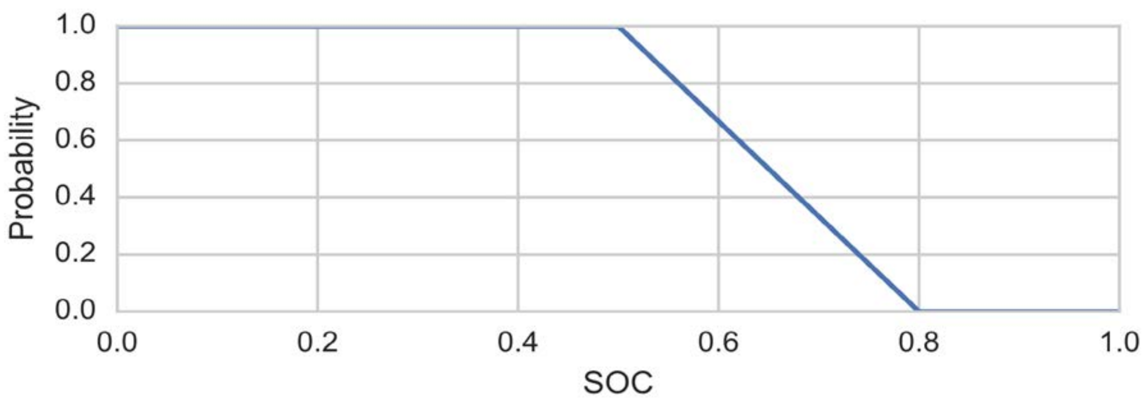
- **Home charger**: probability to have a L1 home charger [0, 1]
- **Work L1 charger**: probability to have a L1 (120 V) work charger [0, 1]
- **Work L2 charger**: probability to have a L2 (208/240 V) work charger [0, 1] – Note: $work\ L1\ charger\ +\ work\ L2\ charger\ <=\ 1$.
- **Other location charger**: probability to have a L2 charger at other location than home or work [0, 1]
- **Vehicle maximum charging rate**: maximum power at which a vehicle can be charged [Watt]
- **Is PHEV**: if FALSE the Nissan Leaf model is used in the simulation, if TRUE the Chevrolet Volt is used in the simulation
- **Ancillary load watt**: constant power demand while driving, it can be seen as additional consumption from the air conditioning system,

- $additional\_energy = ancillary\_load\_watt * driving\_duration\_in\_hour$.

- **Battery efficiency**: represent the energy loss when charging from the grid [0, 1].
- **Climate**: the vehicle consumption is affected by the climate. Three options are available: COLD, TEMPERATE, HOT. Those options map to the consumption (Wh/mi) described in INL vehicle specification sheets (HOT at 95ºF, TEMPERATE at 72ºF, COLD at 20ºF) https://avt.inl.gov/sites/default/files/pdf/fsev/fact2013nissanleaf.pdf
- **[home/work] SOC no charging**: state of charge (SOC) beyond which user doesn't recharge his or her vehicle, even if a charger is available [0, 1]
- **[home/work] SOC charging**: state of charge below which user always recharges his or her vehicle if a charger is available at the location [0, 1]

The probability of plugging a PEV or not when a charging station is available is determined by **SOC no charging** and **SOC charging,** as shown on Figure 3. In this example: soc_no_charging = 0.8, soc_charging = 0.5

Figure 3: The Probability of Plugging a Plug-In Electric Vehicle With a Specific SOC When a Charging Station Is Available



Validation Method

INL's itineraries data set was divided into two data sets, a calibration data set and a validation data set. INL staff adjusted the input parameters to V2G-Sim to make the output of V2G-Sim as close as possible to the actual charging behavior (calibration process). Once the input parameters to V2G-Sim were calibrated, the same inputs were used on the validation data set. This process was followed for all six use cases.

In the charts below, actual charging profiles are compared with profiles from V2G-Sim for the calibration and the validation sets, which are respectively named Calibration Results and Validation Results.

Input Parameters to V2G-Sim

The trained input parameters agree with what has been seen on the EV Project descried on page 11 of this report. For instance, the Chevrolet Volt tends to use L1 charger at work, whereas the Nissan Leaf exclusively uses L2 chargers. This is partially since the Chevrolet Volt comes with an adapter for L1 chargers.

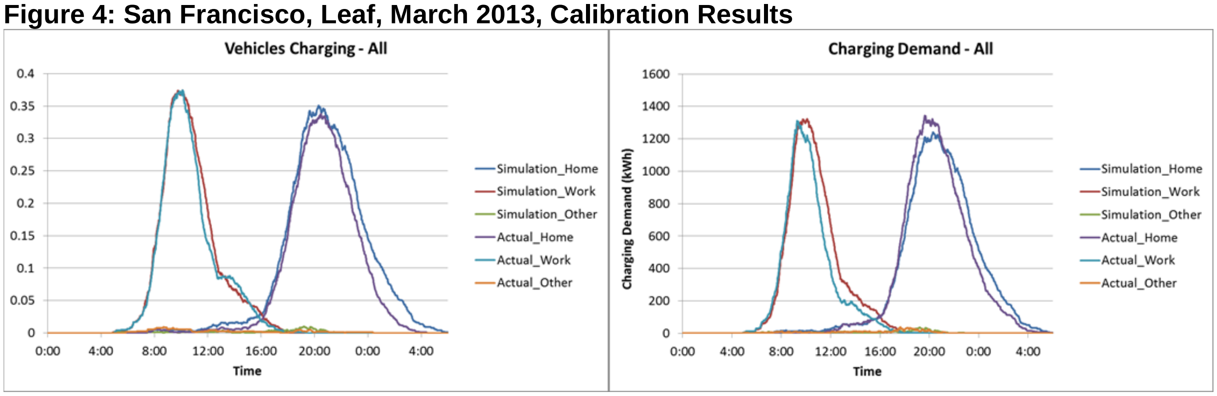
Table 2: Result of the Calibration Process, Best Fit for Each of the Six Use Cases

Itinerary filename	San Fran March Leaf	San Fran Aug Leaf	San Diego Mar Leaf	San Diego Mar Volt	Los Angeles Aug Leaf	Los Angeles Aug Volt
Home charger	1	1	1	1	1	1
Work L1 charger	0	0	0	0.4	0	0.4
Work L2 charger	0.7	0.7	0.78	0.45	0.78	0.4
Other location charger	0.04	0.04	0.04	0.04	0.04	0.04
Home SOC no charging	0.9	0.9	0.9	0.9	0.9	0.9
Home SOC charging	0.5	0.5	0.68	0.6	0.4	0.55
Work SOC nocharging	0.9	0.9	0.9	0.9	0.9	0.9
Work SOC charging	0.7	0.65	0.65	0.65	0.75	0.6
Vehicle max charging rate	3300 W	3300 W	3300 W	3140 W	3300 W	3140 W
Battery efficiency	0.89	0.89	0.89	0.88	0.89	0.88
Is PHEV	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE
Ancillary load watt	200 W	200 W	1500 W	500 W	80 W	800 W
Climate	TEMPERATE	TEMPERATE	TEMPERATE	TEMPERATE	TEMPERATE	TEMPERATE

Note: Parameter description is available in the section named “V2G-Sim input definitions.”
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

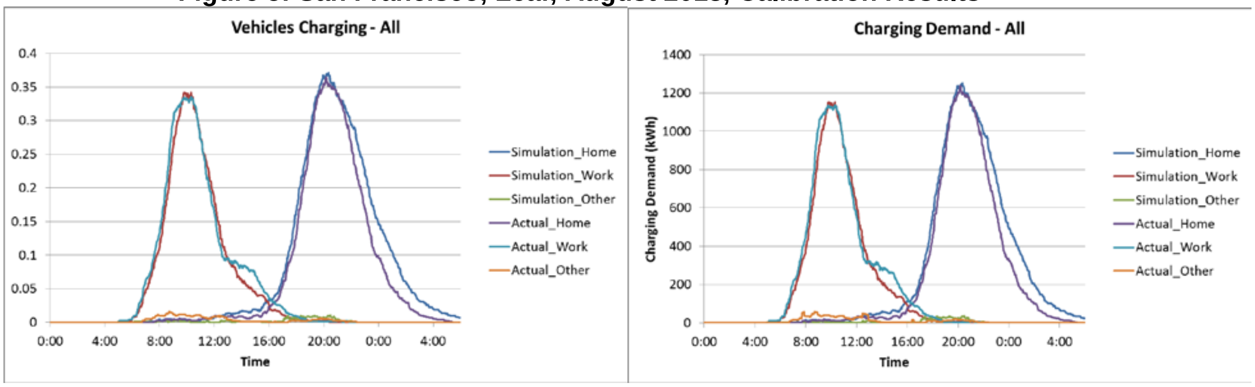
Calibration Results

Figure 4: San Francisco, Leaf, March 2013, Calibration Results



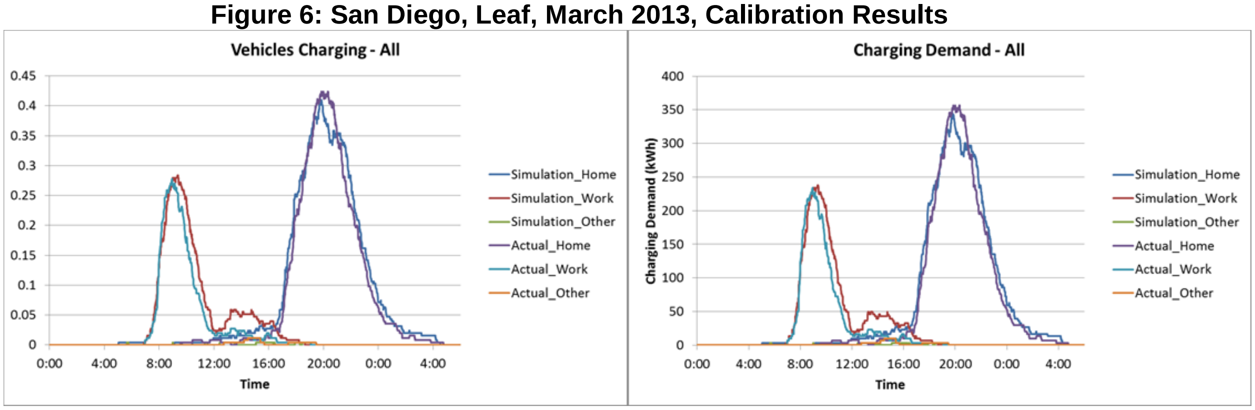
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 5: San Francisco, Leaf, August 2013, Calibration Results



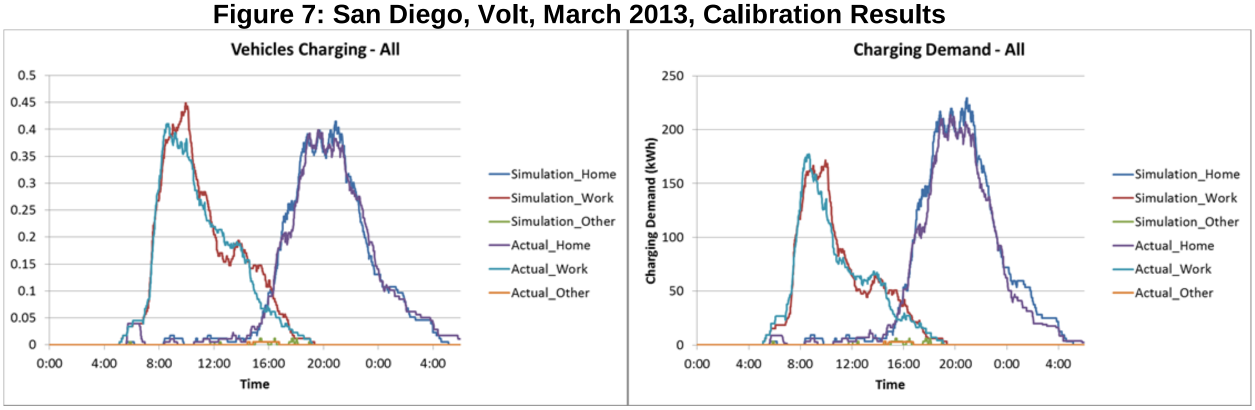
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 6: San Diego, Leaf, March 2013, Calibration Results



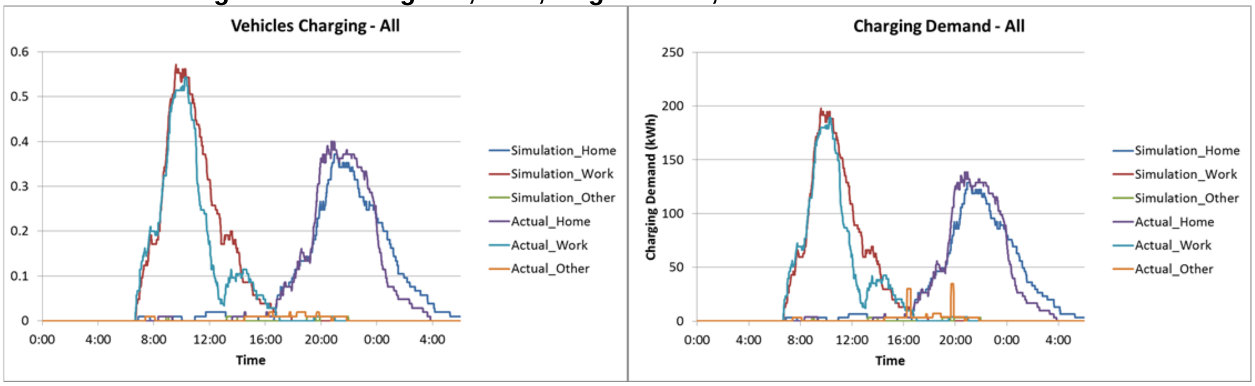
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 7: San Diego, Volt, March 2013, Calibration Results



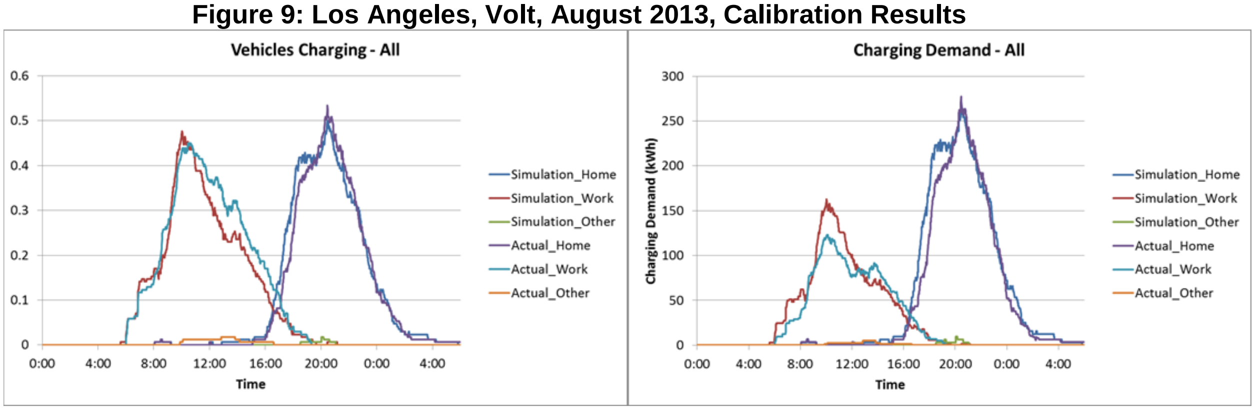
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 8: Los Angeles, Leaf, August 2013, Calibration Results



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

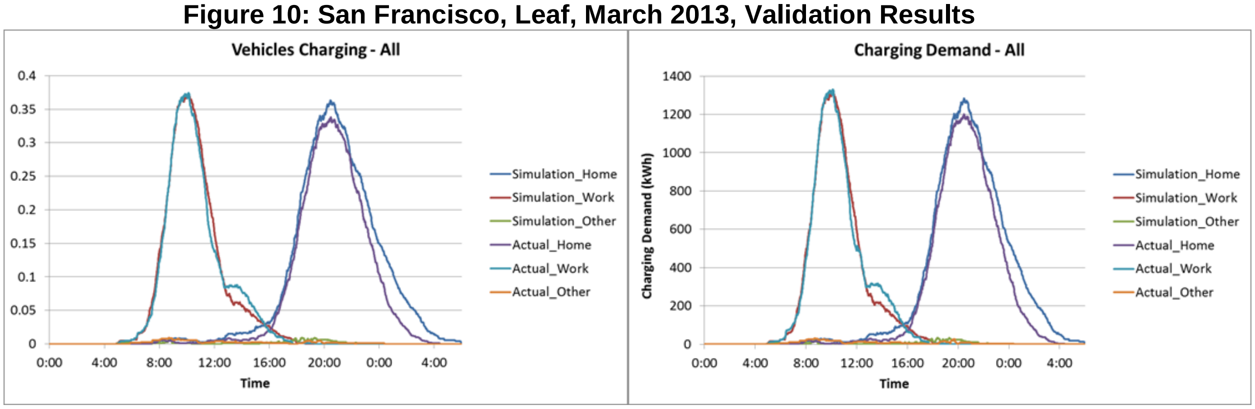
Figure 9: Los Angeles, Volt, August 2013, Calibration Results



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

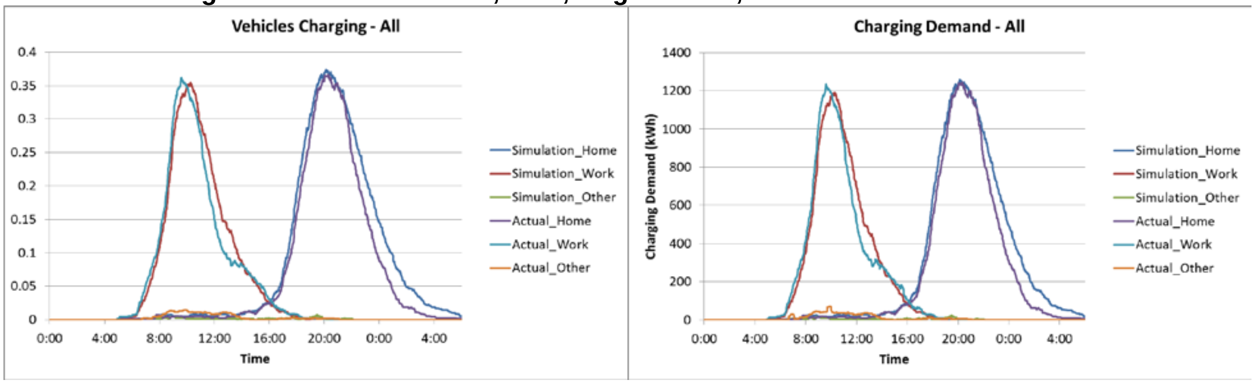
Validation Results

Figure 10: San Francisco, Leaf, March 2013, Validation Results



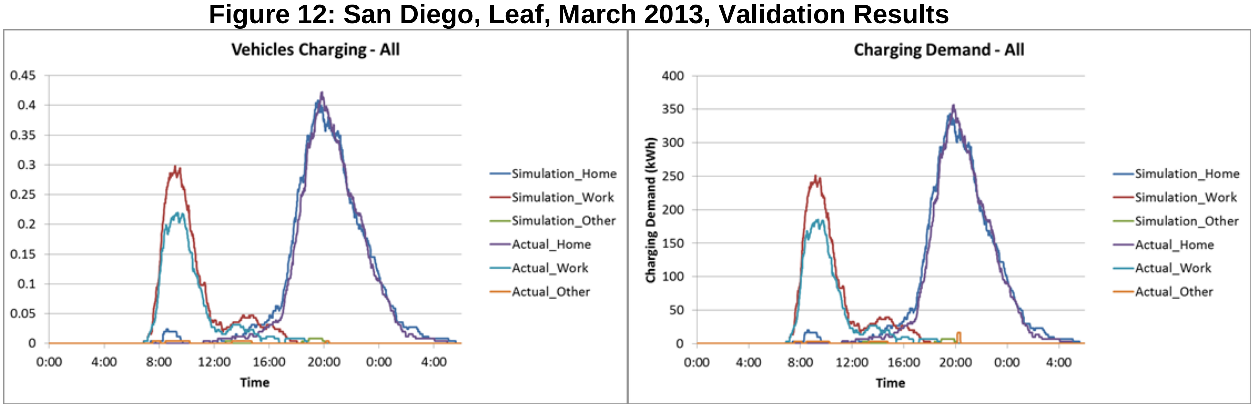
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 11: San Francisco, Leaf, August 2013, Validation Results



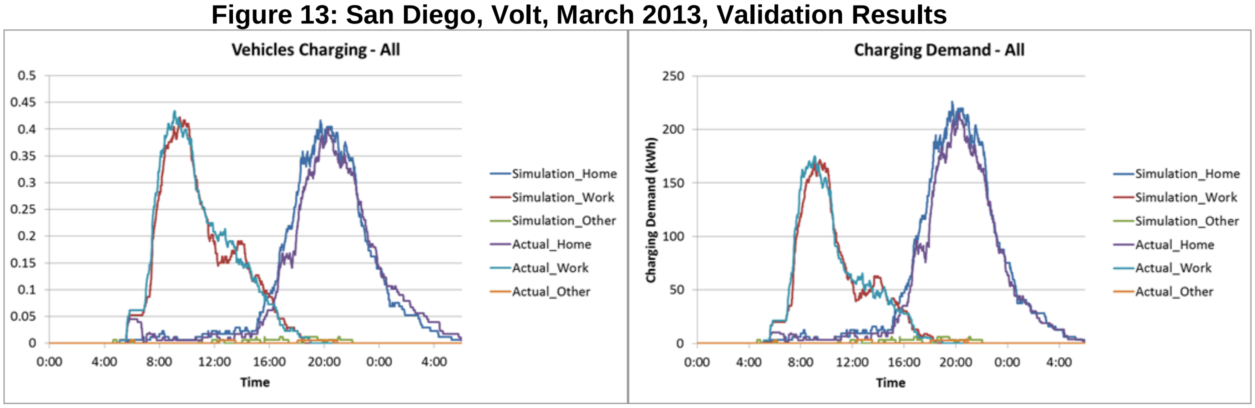
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 12: San Diego, Leaf, March 2013, Validation Results



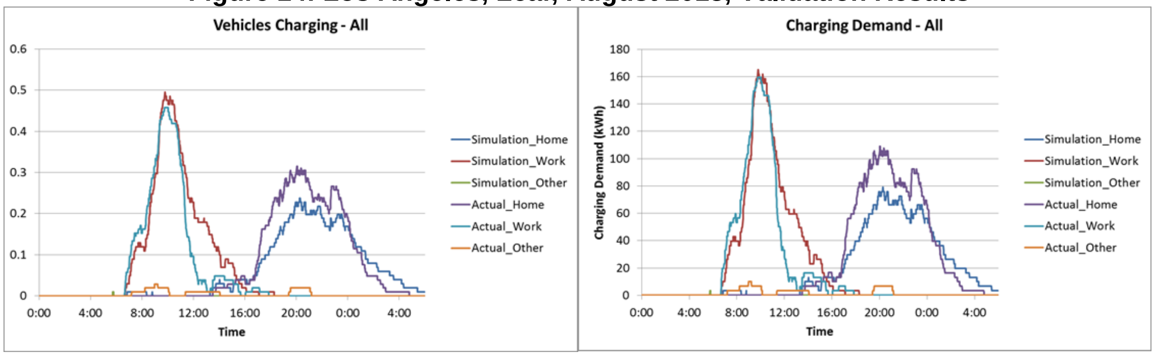
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 13: San Diego, Volt, March 2013, Validation Results



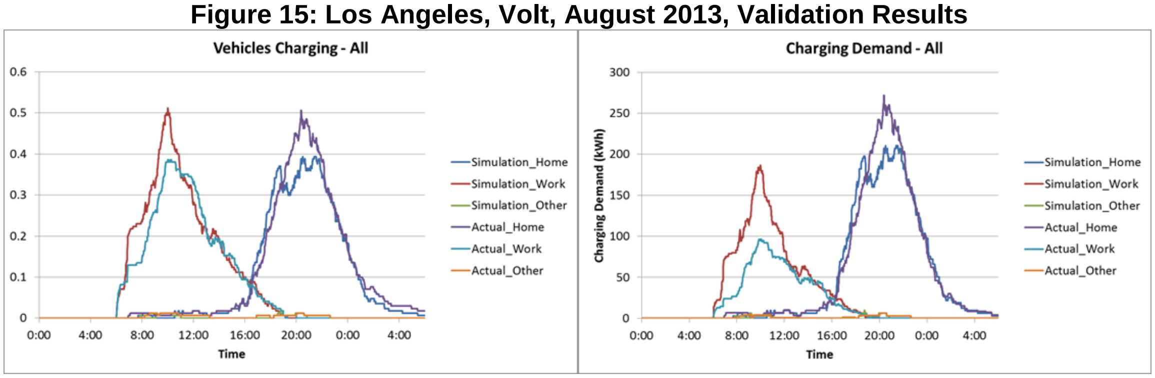
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 14: Los Angeles, Leaf, August 2013, Validation Results



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 15: Los Angeles, Volt, August 2013, Validation Results



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Summary

Looking at the use case comparison charts above, in most cases V2G-Sim can match the actual charging curves reasonably well when given the proper calibration. This achieves the main goal of the validation.

During the calibration, INL staff noticed that the output demand curves from V2G-Sim are sensitive to small changes in a few input parameters:

- The likelihood of a charger being available at home, work, or other locations
- The parameters that describe how the SOC of the vehicle influences the decision of whether to charge when there is a charger available at home and work locations
- The ambient temperature

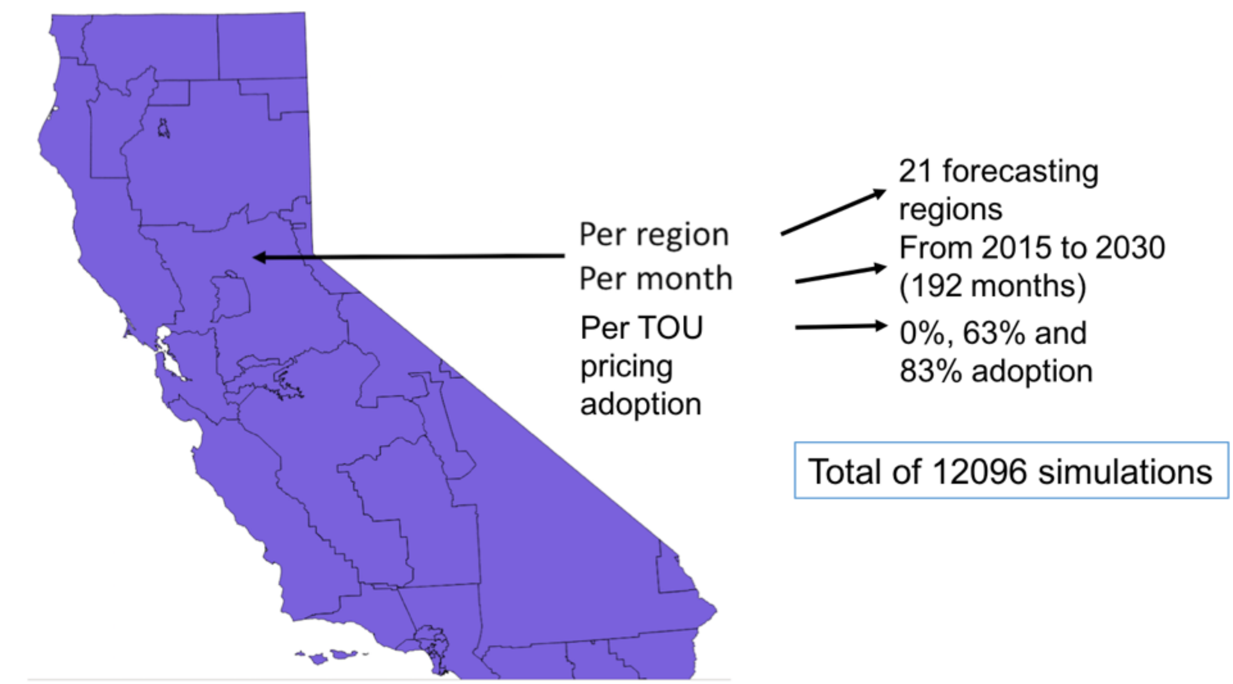
While 1) and 2) tend to shift the power demand between home and workplace locations, 3) tends to increase the magnitude of PEV charging energy as higher temperature increases the use of air-conditioning systems.

As a result, the challenge in using V2G-Sim to forecast future load curves is in estimating the input values accurately. Sensitivity analysis on the input parameters mentioned above may be necessary when using V2G-Sim to construct future load forecasts.

CHAPTER 3: Model-Based Plug-In Electric Vehicles Load Demand Forecast

This chapter explains the method behind the load demand forecast of PEVs. The objective of the forecast is to produce hourly demand profiles for multiple regions from 2015 to 2030 under different assumptions of TOU pricing adoption (0 percent, 63 percent and 83 percent), as shown on Figure 16.

Figure 16: Simulation Matrix for the Plug-In Electric Vehicle Load Forecast

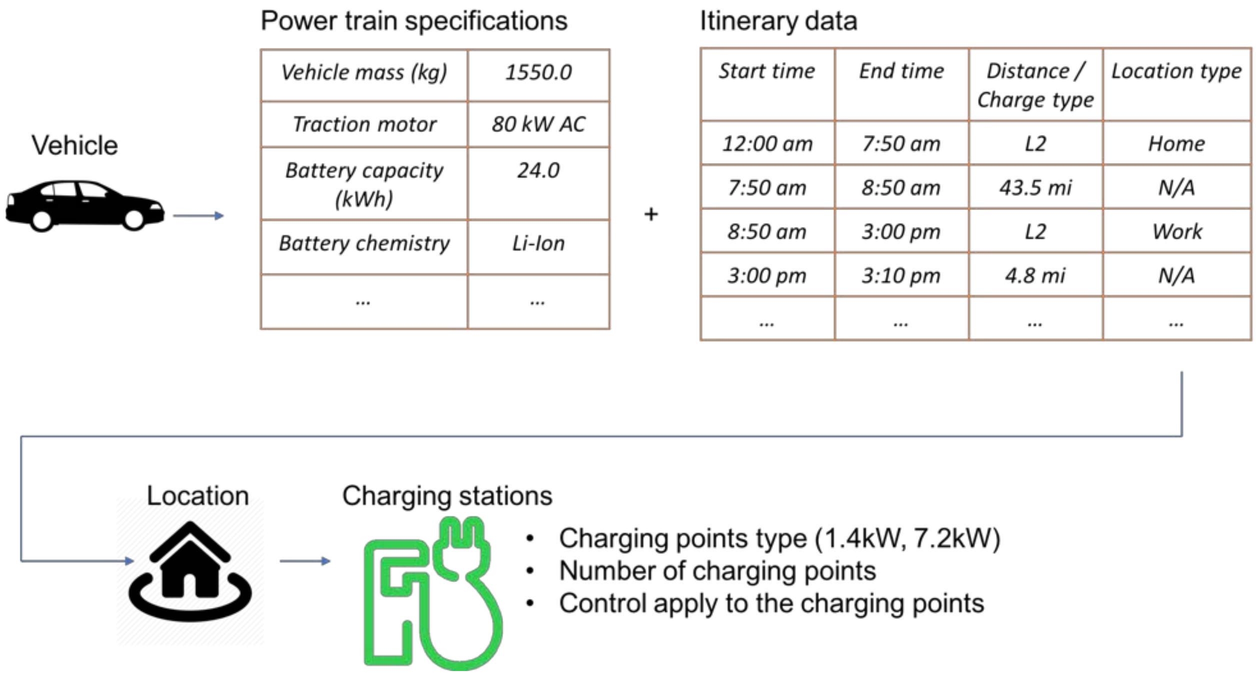


Source: Lawrence Berkeley National Laboratory, Grid Integration Group

The team at LBNL used the V2G-Sim software to simulate PEVs and produce demand profiles. The software was developed at the LBNL and is publicly available at https://github.com/Samveg/V2G-Sim-beta.

V2G-Sim is an agent-based model that provides bottom-up modeling from vehicle dynamics, all the way up to aggregate grid impacts and opportunities. Figure 17 gives an overview of the inputs necessary to run a simulation. The software simulates vehicles based on the physical characteristics (power train specifications) and daily travel patterns (itinerary data). The energy consumed on the grid by the vehicles charging is derived from the number of charging points, associated power constraints, and control algorithm at each location.

Figure 17: Overview of the V2G-Sim Simulation Flow and Necessary Inputs



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

This section is separated into five parts: a description of the inputs and outputs of the model, a description of the vehicle itinerary data, the process of modeling on-road vehicle consumption, charging stations, and the modeling of TOU pricing.

Inputs and Outputs of the Model

This section provides an overview of the data flow from scenario description to simulation results, as summarized in Figure 18.

The first task is to define scenarios for the vehicle stock, the charging infrastructure deployment, the mobility need of PEV owners, and the TOU pricings. The scenarios are based on input forecasts from the Energy Commission. The assumptions made to create each scenario from the forecast data are described in the subsequent sections. Scenarios are described for each month and forecasting zones using four tables (Figure 18):

- Meta information: ambient temperature, increase in the distance traveled
- Charging infrastructures deployment for three types of charger (1.4 kW, 7.2 kW, 100 kW) at each location: number of charging points
- Vehicle stock for each car model: number of vehicles, efficiency factor, battery capacity, maximum charging power
- Electricity prices at each location

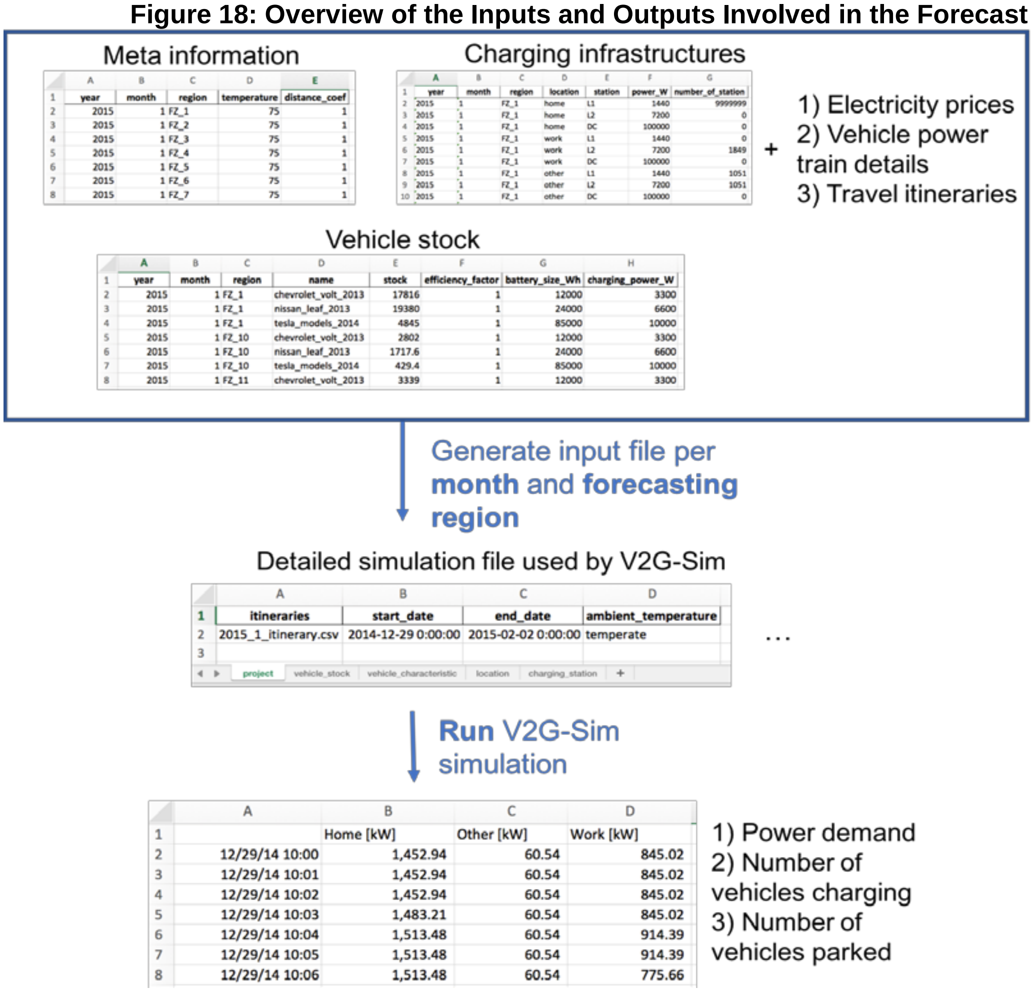
Once the scenarios are defined, the model creates detailed input files compatible with the V2G-Sim input format for each month and each forecasting zone (16 years and 21 forecasting zones lead to 4,032 files). A detailed input file contains information from the above-mentioned four tables and:

- Travel itineraries for the scenario month and forecasting zone.
- Detailed vehicle characteristics for each vehicle.

The next step is to launch a V2G-Sim simulation for each of the 4,032 input files and TOU adoption rates (0 percent, 63 percent and 83 percent) to generate the forecasts. Once a simulation is finished, V2G-Sim produces three time-series with one-minute resolution at each location for a forecasting zone:

- Load shape
- Number of vehicles charging
- Number of vehicles parked

Figure 18: Overview of the Inputs and Outputs Involved in the Forecast



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Travel Itineraries Data

The model uses itineraries to represent when, where, and how far PEV owners travel. The National Household Travel Survey[2] (NHTS) data from California in 2009 are used in this study. The data are formatted as shown in Table 3.

Table 3: Example of a Travel Itinerary Extracted From the National Household Travel Survey

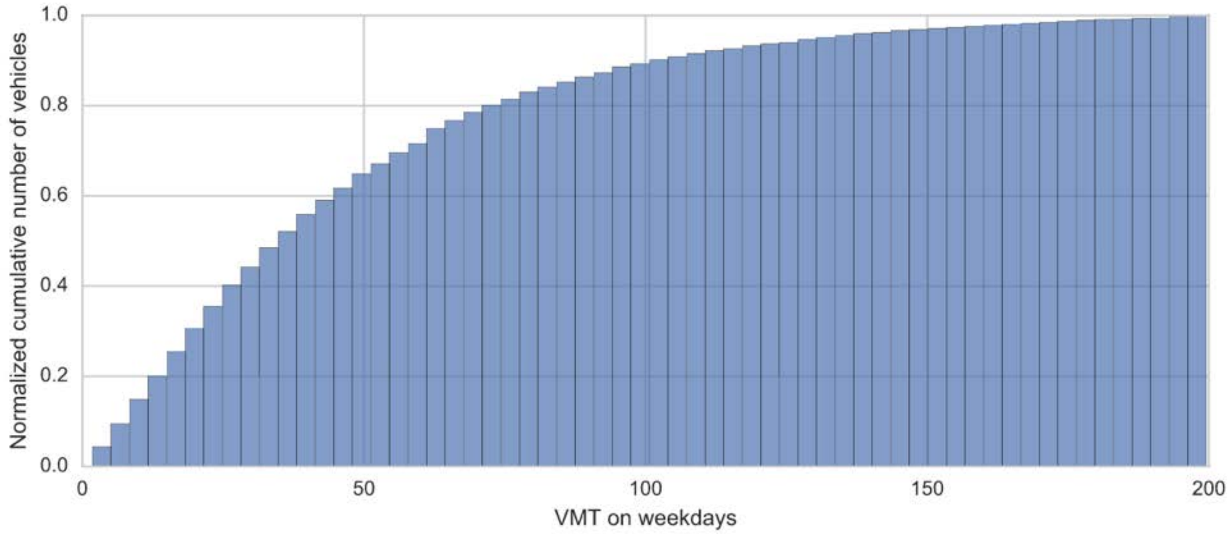
Start Time	End Time	Event Type	Distance	Location Type
12:00 am	7:50 am	Parked	N/A	Home
7:50 am	8:50 am	Driving	43.5 mi	N/A
8:50 am	3:00 pm	Parked	N/A	Work
3:00 pm	3:10 pm	Driving	4.8 mi	N/A
3:10 pm	3:40 pm	Parked	N/A	Restaurant
3:40 pm	3:50 pm	Driving	4.8 mi	N/A
3:50 pm	7:00 pm	Parked	N/A	Work
7:00 pm	7:40 pm	Driving	43.5 mi	N/A
7:40 pm	12:00 am	Parked	N/A	Home

Source: 2009 National Household Travel Survey

The California 2009 NHTS data show a median at 32 vehicle miles traveled (VMT) per day, with 80 percent of the people driving less than 50 VMT per day (Figure 19 and Figure 20).

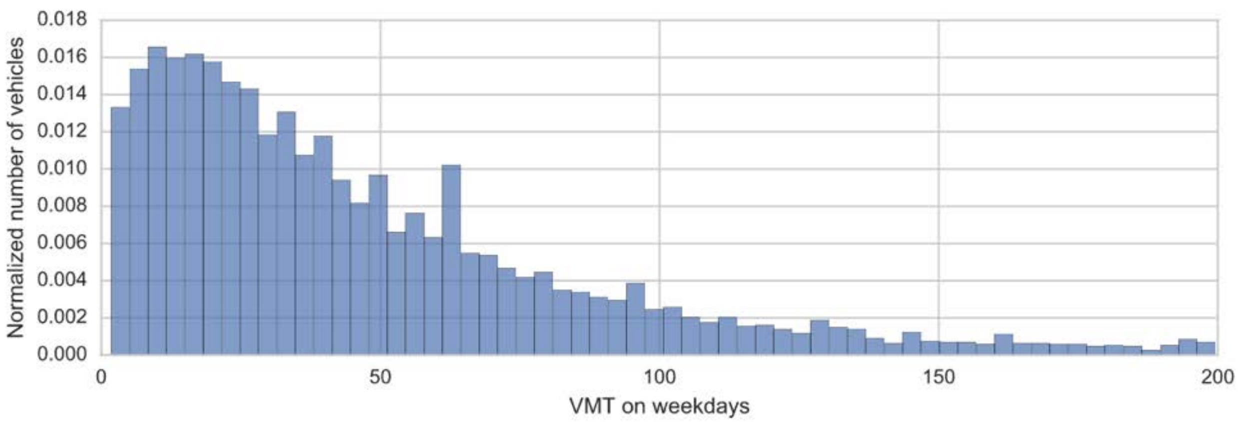
2 https://nhts.ornl.gov/download.shtml.

Figure 19: Cumulative VMT per Day on Weekdays From 2009 California NHTS Data



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 20: Normalized VMT per Day on Weekdays From 2009 California NHTS Data



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Vehicles

On-Road Consumption Modeling

Vehicles are modeled in these simulations. Each vehicle is modeled as a collection of driving and parked events within a given day. Travel itineraries for California drivers from the NHTS are used to obtain unique schedules of events for a representative collection of drivers. (See previous section.)

During driving events, the battery consumption is calculated using the trip distance, trip duration, and a representative average consumption per mile for the trip. The battery state of charge (SOC) at the end of trip j for vehicle i is calculated from Equation 1, where E_i is the battery energy capacity (*Wh*) for vehicle i, and $EC_{i,j}$ is the average electrical consumption (*Wh/km*) for vehicle i on trip j, and d_j is the trip distance:

Equation 1

$$SOC_{i,j} = \frac{\left(SOC_{i,j}(t_0) \times E_i\right) - \left(EC_{i,j} \times d_j\right)}{E_i}$$

To pick an average electrical consumption (*Wh/km*) for trip j, the authors use the trip average speed ($\bar{V}_{i,j}$) to select among three driving cycles: UDDS (Urban Dynamometer Driving Schedule), HWFET (The Highway Fuel Economy Test), and US06 (an aggressive, high-speed and/or high-acceleration driving behavior) (EC_{UDDS}, EC_{HWFET}, EC_{US06}) consumptions, as shown in Equation 2. The average electrical consumption also depends on ambient temperature (*T*), as hotter days imply higher air-conditioning loads.

Equation 2

$$\mathrm{EC}_{i,j} = \begin{cases} EC_{UDDS}(T), \bar{V}_{i,j} < \bar{V}_{UDDS} \\ EC_{HWFET}(T), \bar{V}_{i,j} \geq \bar{V}_{UDDS} \text{ } and \text{ } \bar{V}_{i,j} \leq \bar{V}_{HWFET} \\ EC_{US06}(T), \bar{V}_{i,j} > \bar{V}_{HWFET} \end{cases}$$

Table 4: Drive Cycle Corresponding Average Speeds

Drive cycle name	mean speed [mph]
UDDS	$\bar{V}_{UDDS} = 19.6$
HWFET	$\bar{V}_{HWFET} = 48.3$

Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Parked Vehicle Modeling

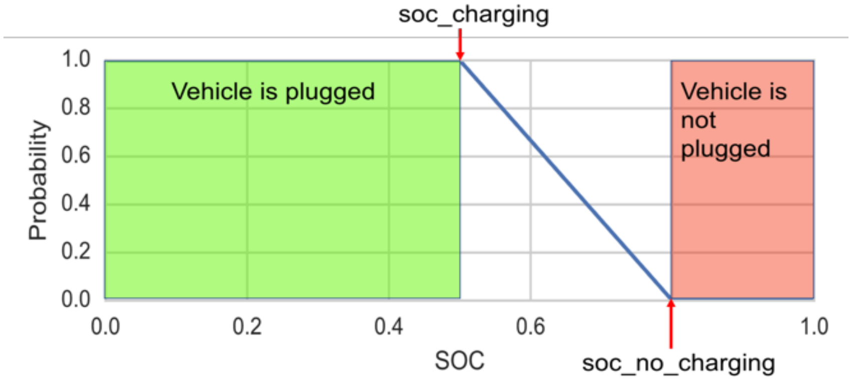
When the vehicle owner parks the vehicle, he or she decides whether to plug. Vehicles tend not to be plugged-in if the associated SOC is high. Thus, the decision to plug is modeled by a probability function that depends on the vehicle SOC, as described in Equation 3.

Equation 3

$$\mathrm{Plugged}_{\mathrm{boolean}} = \begin{cases} True, if \text{ } soc(t) \leq soc_{charging} \\ P(soc), if \text{ } soc(t) > soc_{charging} \text{ } and \text{ } soc(t) < soc_{nocharging} \\ False, if \text{ } soc(t) \geq soc_{nocharging} \end{cases}$$

The probability of plugging a PEV when a charging station is available is a piecewise function determined by "soc_no_charging" and " soc_charging," as shown in Figure 21. The probability to plug a vehicle linearly decrease from 100 percent of the time to 0 percent when the SOC is in-between "soc_charging and "soc_no_charging." In the example shown in Figure 21, soc_no_charging = 0.8 and soc_charging = 0.5, and when a vehicle SOC is at 70 percent, there is a 40 percent change for that vehicle to be plugged.

Figure 21: Example of the Probability of a PEV Plugging Into a Recharge When a Charging Station Is Available



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Fleet Stock Forecast

The fleet forecast includes vehicle stock, battery sizes, and vehicle on-road fuel consumption. (See Tables 5 to 8.) The vehicle stock and the battery size per vehicle class, year, and region were applied in the simulations (Table 6 and Table 7). The on-road fuel consumption from Table 8 was used to generate an efficiency factor; this factor was then used by the V2G-Sim to model the evolution of the on-road consumption throughout the years.

Table 5: California Energy Commission Vehicle Classification and Equivalent Vehicle Model

Year	Brand	Model	Powertrain	CEC Classification
2013	Chevrolet	Volt	PHEV	Car-Compact
2017	Cadillac	CT6	PHEV	Car-Large
2017	Ford	C-Max Energi	PHEV	Car-Midsize
2017	BMW	i8	PHEV	Car-Sport
	BMW	i3	PHEV	Car-Subcompact
2017	Volvo	XC90 T8 Twin Engine	PHEV	Cross/Ut-Midsize
	Volvo	XC90 T8	PHEV	Cross/Ut-Small-Car
2017	BMW	X5 xDrive40e	PHEV	Cross/Ut-Small-Trk
	Workhorse	W15	PHEV	Pickup-Compact
	Land Rover	Range Rover Evoque	PHEV	Sport/Ut-Compact
	Mercedes Benz	GLE 550e	PHEV	Sport/Ut-Midsize
2017	Chrysler	Pacifica Hybrid	PHEV	Van-Compact
	Ford	Transit	PHEV	Van-Std
2013	Nissan	Leaf	BEV	Car-Compact
2014	Tesla	Model S	BEV	Car-Large
2017	Honda	Clarity Electric	BEV	Car-Midsize
	Tesla	Roadster	BEV	Car-Sport
2017	Fiat	500e	BEV	Car-Subcompact
	Mercedes	EQ C	BEV	Cross/Ut-Midsize
2017	Tesla	Model X 75D	BEV	Cross/Ut-Small-Car
2017	Kia	Soul EV	BEV	Cross/Ut-Small-Trk
	Ford	Model E	BEV	Sport/Ut-Compact
	Volkswagen	ID Lounge	BEV	Sport/Ut-Midsize
	Dodge	Caravan	BEV	Van-Compact

Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Table 6: Vehicle Stock per Class, Years and Forecasting Zones (FZ_1)

	2015	2016	2017
1			
Car-Compact	7,641	10,972	13,895
Car-Large	8	57	164
Car-Midsize	10,213	13,703	17,885
Car-Sport	99	210	317
Car-Subcompact	947	1,830	2,645
Cross/Ut-Midsize	-	-	663
Cross/Ut-Small-Car	-	-	-
Cross/Ut-Small-Trk	-	1,012	2,139
Pickup-Compact	-	-	-
Pickup-Std	-	-	-
Sport/Ut-Compact	-	-	-
Sport/Ut-Large	-	-	-
Sport/Ut-Midsize	-	509	1,049
Van-Compact	-	-	1,648
Van-Std	-	-	-

Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Table 7: Vehicle Battery Size in KWh per Vehicle Class and Year

PHEV - LOW, MID, & HIGH CASE					
VEHICLE CLASS	**2015**	**2016**	**2017**	**2018**	**2019**
Car-Subcompact	24.2	24.2	33.2	33.2	33.2
Car-Compact	17.1	16.8	16.8	15.3	15.0
Car-Midsize	6.5	7.8	8.4	9.3	10.0
Car-Large	9.3	8.9	14.0	11.4	12.8
Car-Sport		7.1	7.1	10.2	10.2
Cross/Ut-Small-Car				8.6	8.6
Cross/Ut-Small-Trk	10.8	9.4	9.4	11.1	11.2
Cross/Ut-Midsize		9.2	9.2	10.4	10.4
SUV-Compact					10.0
SUV-Midsize		8.8	8.8	8.8	12.6
SUV-Large					
Pickup-Compact					40.0
Pickup-Std					
Van-Compact			16.0	16.0	16.0
Van-Std					

Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Table 8: Vehicle Efficiency in MPGe per Vehicle Class and Year

BEV - LOW & MID CASE				
VEHICLE CLASS	**2015**	**2016**	**2017**	**2018**
Car-Subcompact	90.2	90.0	86.7	86.9
Car-Compact	81.9	83.0	93.1	96.5
Car-Midsize	85.8	86.7	92.9	98.9
Car-Large	78.3	80.4	80.9	81.3
Car-Sport				
Cross/Ut-Small-Car		75.0	74.7	82.0
Cross/Ut-Small-Trk	82.2	82.2	82.2	85.9
Cross/Ut-Midsize				
SUV-Compact				
SUV-Midsize				
SUV-Large				
Pickup-Compact				
Pickup-Std				
Van-Compact				
Van-Std				

Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Charging Station

Charging Vehicle Modeling

During parked events, vehicles can either be plugged in or parked without being plugged in. When a vehicle is not plugged in, the associated charging rate is set to zero for the duration of the parking. When a vehicle is plugged, it charges at full power from the time when it was plugged in until it either reaches a full charge or unplugs for the next trip. The power transfer rate is determined by the type of charger the vehicle is plugged into, that is 1.4 kW for L1 chargers, and 10 kW for L2 chargers, but also by the vehicle limitation. (That is 3.3 kW for the Chevrolet Volt.)

The time-resolved charging power profile for vehicle *i* in charging session *j* is calculated using Equation 4, and the battery SOC is calculated with Equation 5, where P_{max} is the maximum charging rate for the type of charger used in the charging session (depending on the type of charger and the vehicle limitation):

Equation 4

$$P_{charge,i,j}(t) = \begin{cases} P_{max}\,, & SOC_{i,j}(t-1) < SOC_{max} \\ 0, & SOC_{i,j}(t-1) = SOC_{max} \end{cases}$$

Equation 5

$$SOC_{i,j}(t) = SOC_{i,j}(t-1) + \frac{P_{charge,i,j}(t) \times \Delta t}{E_i}$$

Each vehicle *i*'s energy interactions are calculated by sequentially computing the SOC and charging power profiles for driving and charging events *j*. By summing the charging power $P_{charge}(t)$ in Equation 6 across all *i* vehicles, the total grid charging or discharging load is calculated.

Equation 6

$$P_{vehicle-grid}(t) = \sum_{i=1}^{V} P_{charge,i}(t)$$

Charging Station Forecast

The charging station forecast includes each forecasting zone (FZ), year, location (residential, work, and public), and charger type (L2 and DC fast charging). A sample of the charging station forecast is shown in Table 9. These quantities represent the number of charging points; this is then converted to a probability of having access to charging infrastructure, as defined in Equation 7. The probability of access at a location is defined by the number of charging stations divided by the total number of vehicles throughout the day. Since multiple vehicles use the same charger at different times of the day, the numerator is multiplied by the number of daily uses for a typical charger (*nb_usages_per_day*). Data analysis from real-world measures (Chapter 1) show an average of three to four unique vehicles per day, which was increased to seven, given the low number of charging stations in the forecast potentially inducing a faster turnaround of the vehicles. The availability of charging points at a location is then used by V2G-Sim to assign vehicles to available charging stations.

Equation 7

$$charger\ availability_{location} = \frac{nb\ charging\ points\ _{location} \times nb\ usages\ per\ day}{nb\ vehicles\ _{location}}$$

Table 9: Number of Charging Points per Forecasting Zones (FZ), Year and Location (Residential, Work, Public)

FZ	L2 res mf 2028	L2 work 2028	L2 public 2028	L2 res mf 2029	L2 work 2029	L2 public 2029
0	10	41	109	11	46	123
1	1952	3478	4420	2189	3899	4958
2	321	435	1118	360	489	1255
3	46	145	277	51	162	309
4	508	1058	1864	572	1187	2089
5	160	667	951	179	748	1067
6	182	448	816	204	503	916
7	2371	5211	4848	2659	5843	5436

Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Response to Time-of-Use Pricing (TOU)

TOU Response Modeling Method

Time-of-use pricings create incentives for PEV owners to charge their vehicles when electricity prices are the lowest. To model drivers' response to TOU pricings, the authors introduce a variable describing the price a PEV owner is willing to pay for energy depending on the vehicle SOC.

During the charging, if the price of electricity rises above a threshold defined by the vehicle owner for a given state of charge, the vehicle stops drawing power from the grid. For this simulation, every vehicle owner implements the same price threshold. Once the electricity price has decreased, the charging can be resumed, as described in Equation 8.

Equation 8

$$P_{charge,i,j}(t) = \begin{cases} P_{max}\ , & price_{electricity} \leq price_{threshold} \\ 0, & price_{electricity} > price_{threshold} \end{cases}$$

P_{max} is the maximum charging rate for the type of charger used in the charging (depending on the type of charger and the vehicle limitation). Equation 8 describes the effect of the price threshold on the vehicle load shape. The effect of this control is to prevent vehicles from charging when electricity prices are high, unless the state of charge is low.

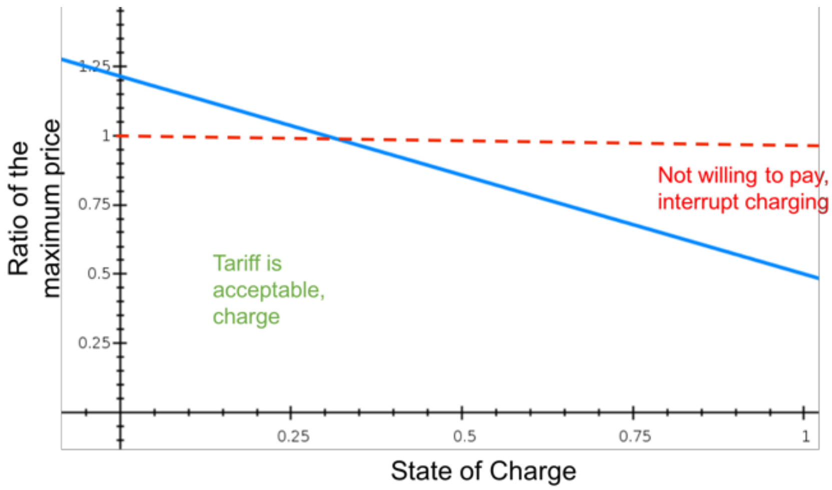
The price threshold implemented for this forecast is expressed relatively to the highest price per month, $price_{threshold} \in [0,1]$ where $price_{threshold} = 1$ represents the highest price in the month. (See the dashed red line in Figure 22.) Equation 9 defines the relationship between the threshold price and the state of charge of a vehicle. The coefficients used in Equation 9 ensure that vehicles are always plugged if possible, when they have less than 35 percent of remaining charge. For example, Equation 9 and

Figure 22 show that a vehicle with a state of charge of 70 percent would accept to charge only if the price is lower than or equal to 71.4 percent of the highest monthly price. Equation 9 is represented by the blue line in Figure 22.

Equation 9

$$\boldsymbol{price_{threshold} = -0.714 \times SOC + 1.214}$$

Figure 22: TOU Pricing Impact on Vehicle Charging



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

The electricity prices including the time-of-use data are defined per forecasting region from 2015 to 2030 with an hourly resolution. Table 10 shows a sample of the file received from the Energy Commission. The date format is “DayMonthYear:Hour:Minute.”

These data are directly used in the simulation to decide when is the best time for a vehicle to charge on the grid, using the method described above.

Table 10: Sample Data of the TOU Pricing Forecast

	A	B	C	D	E
1	datetime	FZ_1	FZ_2	FZ_3	FZ_4
42	02JAN15:16:00	0.240378	0.240378	0.240378	0.240378
43	02JAN15:17:00	0.240378	0.240378	0.240378	0.240378
44	02JAN15:18:00	0.240378	0.240378	0.240378	0.240378
45	02JAN15:19:00	0.240378	0.240378	0.240378	0.240378
46	02JAN15:20:00	0.240378	0.240378	0.240378	0.240378
47	02JAN15:21:00	0.1388843	0.1388843	0.1388843	0.1388843
48	02JAN15:22:00	0.1388843	0.1388843	0.1388843	0.1388843
49	02JAN15:23:00	0.1388843	0.1388843	0.1388843	0.1388843

Source: Lawrence Berkeley National Laboratory, Grid Integration Group

EV Load Shift in Response to TOU Rates

There are two key assumptions in estimating the percentage of load that will shift in response to TOU rates: the percentage of customers enrolled in a TOU rate and the responsiveness of those customers to the price signal. Further, responsiveness of customers will vary depending on whether they are engaged customers who have chosen a TOU rate (opt-in) or defaulted to the rate and, hence, more likely to be unaware or unengaged in responding to the time signal. About 60 percent of EV owners are on a TOU rate by choice. For EV owners who have opted into a TOU rate, various studies have found that between roughly 75 to 90 percent of load is shifted in response to the TOU rate. This range is used to develop projections of the percentage of load shifted for each scenario.

Beginning in 2019, many additional EV owners are likely to be defaulted to a TOU rate. There is no empirical research on how EV owners who are defaulted to TOU rates will respond, but based on the SMUD Smart Pricing Options Pilot, defaulted customers are assumed less responsive than opt-in, with this assumption varying from 10 percent to 35 percent less responsiveness across scenarios.

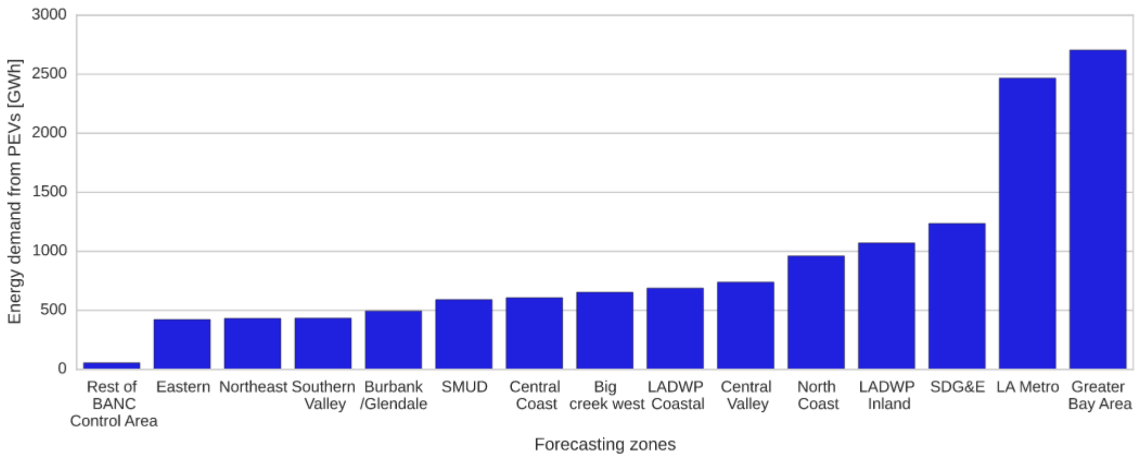
The low demand case assumes that there are no EV owners on TOU rates. In the other two scenarios, it is assumed that 60 percent of EV owners opt into a TOU rate and 90 percent of the remaining 40 percent will be defaulted. In the mid case, it is assumed that EV owners who are opt-in TOU customers will shift 90 percent of their, load while EV owners who are defaulted to a TOU rate will shift 81 percent of their load (assuming customers who are defaulted are 10 percent less responsive than opt-in). Constructing a weighted average of the two groups, 63 percent of load is shifted under these assumptions.

In the high demand case, 75 percent of opt-in TOU EV load is shifted and only 49 percent of defaulted load, for a combined load shift of 83 percent.

CHAPTER 4: Simulation Results

The results of the simulations include the number of vehicles parked or charging and the power demand for all the forecasting zones, from 2015 to 2030, and three TOU adoption rates with one-minute resolution. Figure 23 shows the total energy consumed from PEVs on the grid in 2030 for the different forecasting zones; only regions with a consumption greater than 50 GWh per year were plotted. The study also highlights an added power demand of about 3 GW at 8 p.m. in 2030 for the whole California TOU prices creates a sharp increase or decrease of the power demand when tariffs are changing. In this case, the peak power demand goes from 2.6 GW with no TOU pricing to 3.5 GW at 83 percent of adoption for TOU pricing (Figure 24).

Figure 23: Energy Demand From PEVs for 2030 and for the Forecasting Zones With a Demand Greater Than 50 GWh



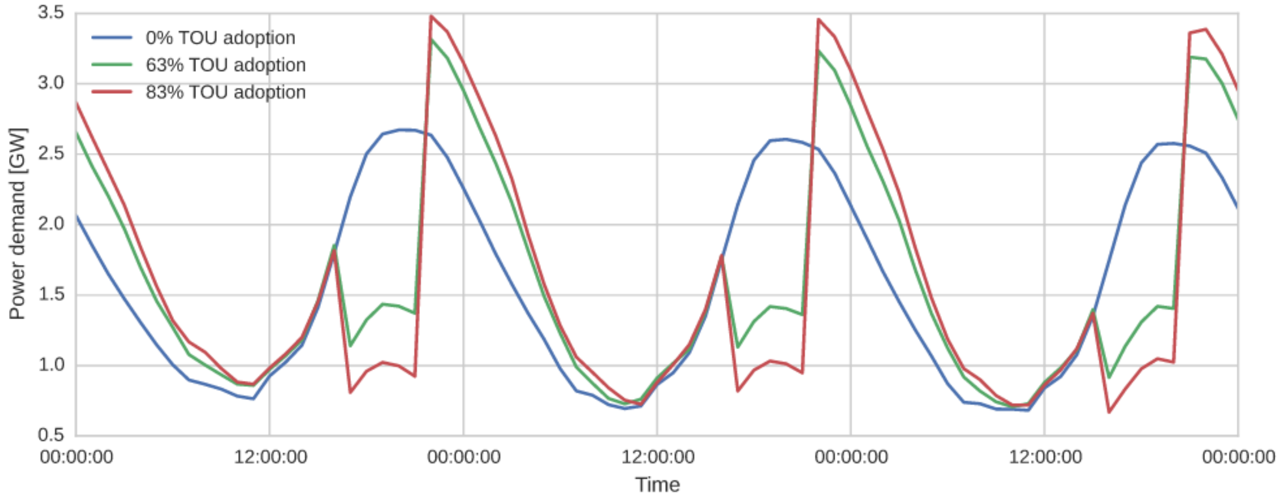
Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Sensitivity Analysis

In this section, the variation in the forecasted power profile-related TOU prices, weather data, type of vehicles, type of charging stations, distance traveled are discussed.

TOU prices create a sharp increase or decrease of the power demand when tariffs are changing. In this case, the peak power demand goes from 2.6 GW with no TOU pricing to 3.5 GW at 83 percent of adoption for the TOU pricing (Figure 24).

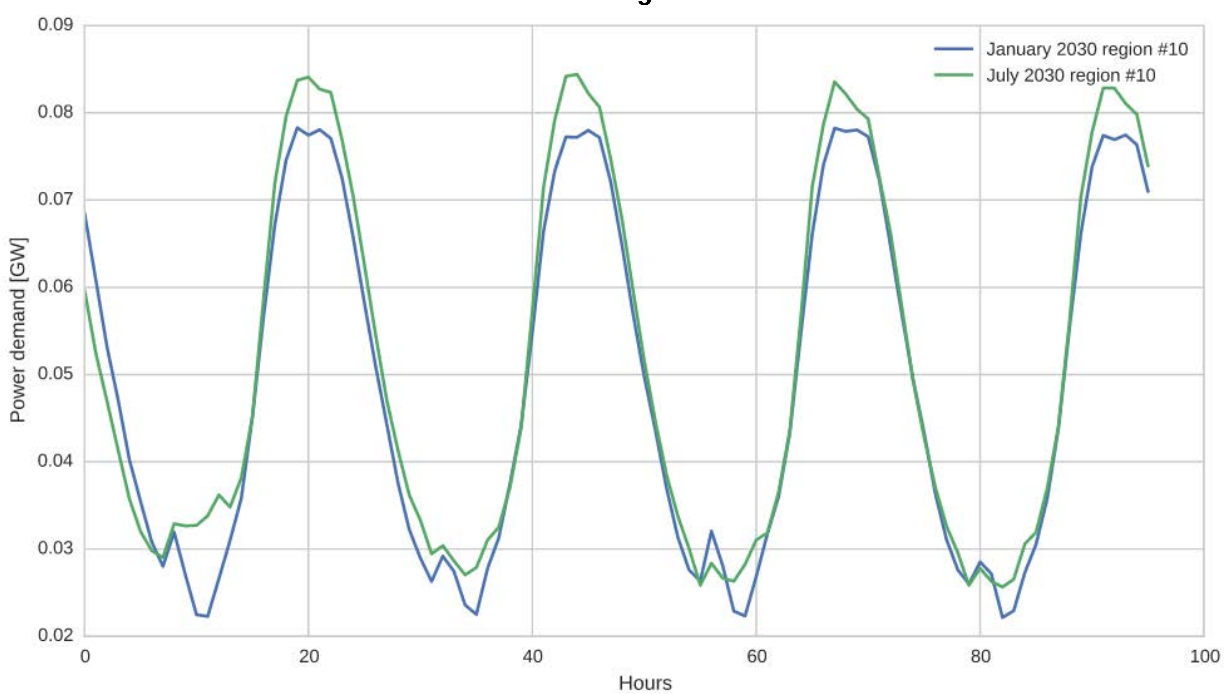
Figure 24: Total Power Demand From PEVs Under Different TOU Adoption Rates, Hourly Data From June 17 to June 20, 2030



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Figure 25 shows the difference in power consumption from "temperate" to "hot." The climate of Forecasting Zone 10 goes from "temperate" in the winter to "hot" in the summer. As the temperature raises, vehicles tend to increase energy consumption to cool the cabin.

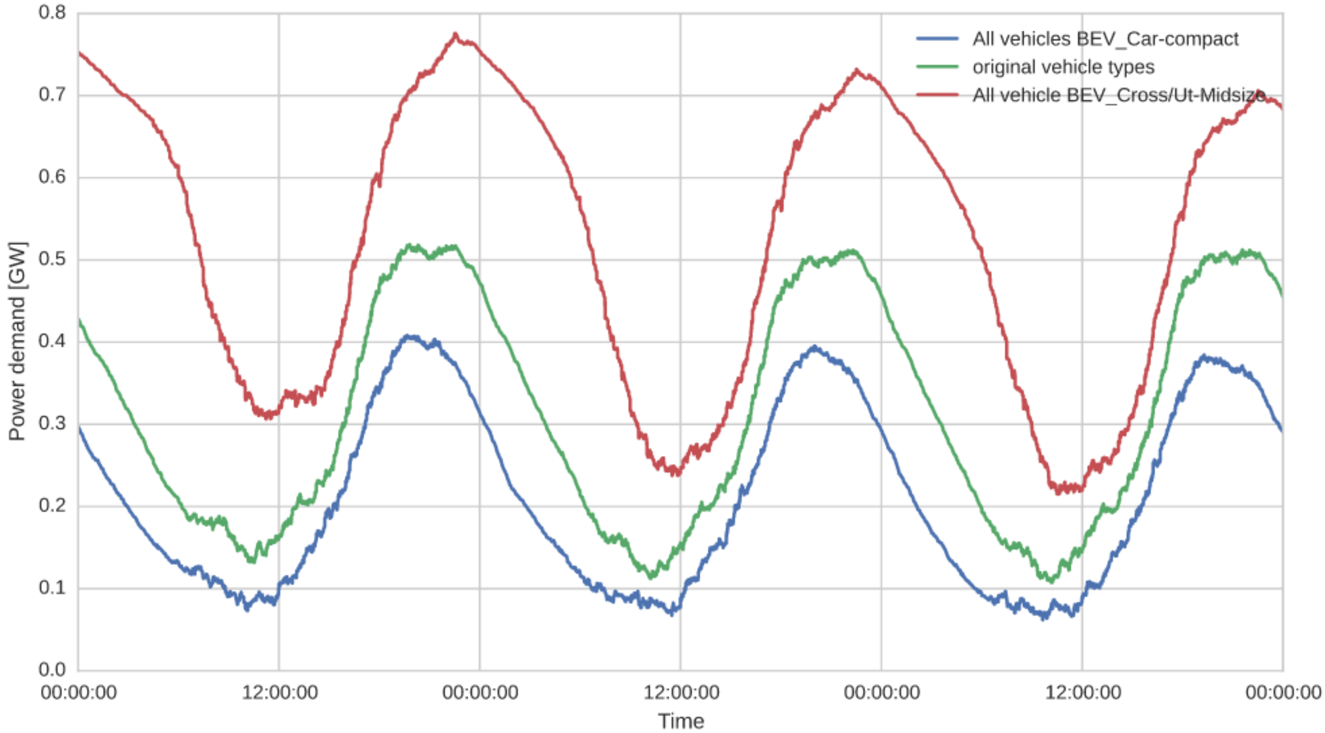
Figure 25: Power Demand From Forecasting Zone 10 for January and July, Hourly Data, No TOU Pricing



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

The vehicle stock defines the number of vehicles in each vehicle class. As the number of vehicles with higher on-road consumption increases, the overall power demand on the grid increases, too. In this case, Figure 26 shows that for a vehicle mix composed of battery-electric vehicles with a higher on-road consumption such as the Mercedes EQ, the peak power demand increase by 40 percent to 60 percent in comparison with the original vehicle mix from 2030.

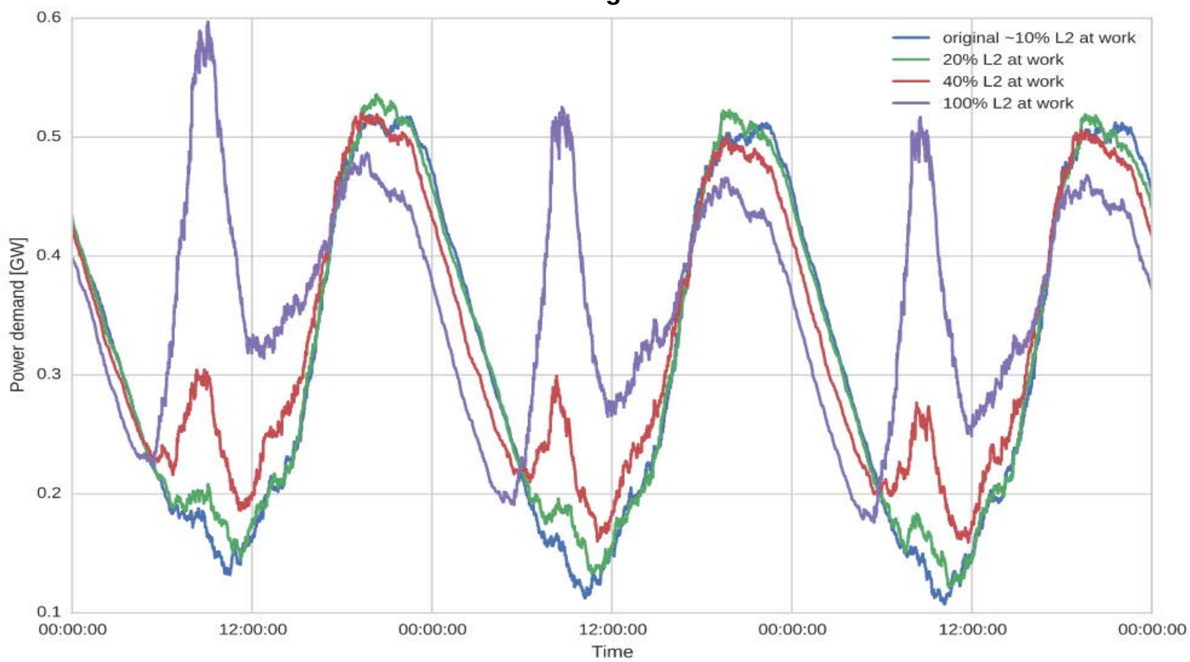
Figure 26: Power Demand From Forecasting Zone 1 for Different Vehicle Stocks, Minute-by-Minute Data From June 17 to June 20, 2030, No TOU Pricing



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

The charging infrastructure is the bridge between the vehicles and the grid; as the penetration of chargers at different locations changes, the shape of the power demand changes. For instance, when charging stations are more available at workplaces, power demand increases at 8 a.m. followed by a reduction of the 8 p.m. peak demand at home locations. When every PEV owner charges his or her vehicles at the workplace (purple line on Figure 27), PEVs peak demand is shifted from around 8 p.m. to 8 a.m.

Figure 27: Power Demand From Forecasting Zone 1 for Different Penetration of L2 Chargers at Workplaces, Minute-by-Minute Data From June 17 to June 20, 2030. No TOU Pricing

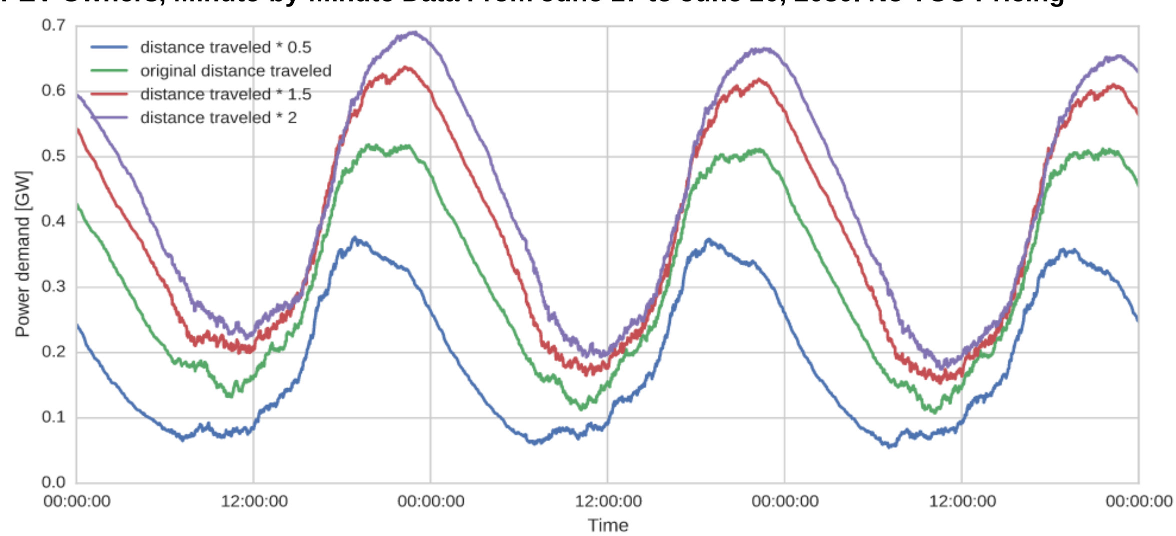


Source: Lawrence Berkeley National Laboratory, Grid Integration Group

The distance traveled is given by the 2009 NHTS. As the authors increase the distance traveled by PEV owners, the on-road consumption increases, which is reflected in the power demand (Figure 28).

On the one hand, vehicle mix and distance traveled directly affect the total energy demand from PEVs. On the other hand, TOU pricing and charging infrastructure have a direct influence on the shape of power demand.

Figure 28: Power Demand From Forecasting Zone 1 for Different Traveled Distances From PEV Owners, Minute-by-Minute Data From June 17 to June 20, 2030. No TOU Pricing



Source: Lawrence Berkeley National Laboratory, Grid Integration Group

Shortcomings of the Simulation

In this section, the biases and shortcoming of the simulation in representing future vehicle charging behavior is highlighted. The parameters that were not adequately captured in the analyses are identified, as well as the parameters that could be incorporated in future studies.

The number of charging infrastructures at workplaces is a critical input that is hard to forecast. In the results, charging at workplaces tends to decrease as vehicles outgrow the number of chargers.

In the hypothesis that the number of chargers at workplaces is doubled in comparison with the current charger forecast, PEV owners in 2030 would have a 20 percent chance to find a charger at work. The resulting load shape (green line on Figure 27) would remain similar to the current scenario in term of peak demand.

Itineraries are key to forecasting total energy and power demand over time. The itineraries dataset used in this study was created in 2009. A more recent and larger sample of itineraries would increase the confidence in the results. The itineraries used here include internal combustion vehicles, which might have different driving patterns than electric vehicles.

This study was done using the vehicle classes provided by the Energy Commission to differentiate vehicle types. Each class aggregates multiple vehicle models. While vehicle models within the same class have similar on-road consumption, they can vary in battery capacity and maximum charging power, which can create significant differences.

The drivers' behavior with the charging station has been modeled based on the SOC of the vehicle. If the SOC is high, PEV owners might not plug their vehicle or at least expect a low electricity price, and vice-versa; when the SOC is low, PEV owners are likely to plug their car and willing to pay more for electricity. The behavior model was calibrated with the ChargePoint data from INL. It would be interesting to further develop this calibration process with more data and forecast how it might evolve.

The model simulates vehicles charging as soon as they arrive when they have access to a charger. In the future, charging vehicles might be a completely autonomous task. Thus, while the energy demand might remain similar to the forecast, the load shape could be very different as vehicles would coordinate charging with the grid.

CHAPTER 5: Conclusion

In this study, the research team analyzed real-world data from PEV charging behavior. A PEV load simulation tool was developed to process inputs such as vehicle stocks, infrastructure deployment, temperature data, and driving patterns to estimate a corresponding power demand on the grid. The team used real-world data to validate and calibrate the PEV load demand simulation tool. Finally, the authors launched simulations to forecast PEVs load demand from 2015 to 2030 for 21 forecasting zones under three TOU adoption rates with one-minute resolution. Overall, the study shows an added 3 GW of power demand from PEVs at 8 p.m. on the grid in 2030.

In the current forecast, PEVs are charged as soon as possible. However, in the future, as PEVs are coordinated to support the grid, the associated load shape could be very different. Future work involves refining the validation and calibration of the simulation tool from a larger set of real-world measurements. Improvements of the modeling capabilities of the simulation tool are also envisioned, as the current version laid the foundations of a plug-and-play architecture composed of modules that can continuously be improved. Special attention should be given to the scalability of the model, as improvements on this side will allow the inclusion of more detail modeling of the vehicles. Future results should also include uncertainties to reflect the nature of the inputs. A possible solution would be to generate high, medium, and low scenarios for each simulation.

Glossary of Terms:

Agent-based simulation: An agent-based model is a class of computational models for simulating the actions and interactions of autonomous agents with a view to assessing the related effects on the system as a whole.

Battery capacity: The battery capacity represents the maximum amount of energy that can be extracted from the battery under certain specified conditions.

California ISO: The California Independent System Operator (California ISO) is a nonprofit independent system operator (ISO) serving California. It oversees the operation of California's bulk electric power system, transmission lines, and electricity market generated and transmitted by its member utilities.

Charging infrastructure: An electric vehicle charging station – also called EV charging station, electric recharging point, charging point, charge point and EVSE (electric vehicle supply equipment) – is an element in an infrastructure that supplies electric energy for the recharging of electric vehicles

Distribution grid: The distribution grid is the final stage in the delivery of electric power; it carries electricity from the transmission system to consumers.

EVSE: Electric vehicle supply equipment; see *charging infrastructure*.

Itinerary: An itinerary is a detailed plan of all the routes taken by a vehicle, including start and end time, as well as distance traveled.

Load shape: A load shape is a graph of the variation in the electrical load versus time. Power producers use this information to plan how much electricity they will need to make available at any given time.

PEVs: A plug-in electric vehicle is any motor vehicle that can be recharged from an external source of electricity, such as wall sockets, and the electricity stored in the rechargeable battery packs drives or contributes to drive the wheels.

Power grid: A power grid is an interconnected network for delivering electricity from producers to consumers.

Powertrain: In a motor vehicle, a powertrain describes the main components that generate power and deliver it to the road surface.

SOC: State of charge is the equivalent of a fuel gauge for the battery pack in a battery electric vehicle. The units of SOC are percentage points (0% = empty; 100% = full).

Time of use tariff: Time-of use (TOU) tariff pricing plan means your electricity rates are changing in time (peak and off-peak tariffs).

Transmission grid: Electric power transmission is the bulk movement of electrical energy from a generating site, such as a power plant, to an electrical substation. This is distinct from the local wiring between high-voltage substations and customers, which is typically referred to as *electric power distribution*. The combined transmission and distribution network is known as the "power grid."

Abbreviations and Acronyms:

California ISO: California Independent System Operator

Energy Commission: California Energy Commission

EVSE: Electric vehicle supply equipment

INL: Idaho National Laboratory

LBNL: Lawrence Berkeley National Laboratory

NHTS: National Household Travel Survey

L1: Level 1 charger

L2: Level 2 charger

PEV: Plug-in electric vehicle

PHEV: Plug-in hybrid electric vehicle

SUV: Sport utility vehicle

SOC: State of charge

TOU: Time of use